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Investigations of Cardiac Rhythm Fluctuation Using the DFA Method

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Abstract

Considering the highly nonlinear and non stationary features of the ECG signal proven by latest researches, the most appropriate methods of analysis are based also on the nonlinear dynamics; we used a modified root mean square analysis of a random walk, named detrended fluctuations analysis (DFA), which proved efficacy as diagnostic tool and advantages on the existing related methods.

Our studies were conducted on two groups of young and old subjects, totally 24 patients, and the different behavior being related to the underlying dynamics of the heartbeat.

We compare the data results using the DFA method: first when a line segment is fitted and second, when a quadratic polynomial is fitted in the least-squares sense

Applications of this analysis may lead to new and safe diagnosis for patients and to evaluation of the patient status in systemic diseases that may affect in time the cardio-vascular system.

Keywords: Cardiac rhythm; Heart rate variability; Nonlinear Dynamics; Detrended Fluctuation Analysis.

I. Introduction

The human heart is a complex spatiotemporal dynamic system, about which we know little. In spite of great progress of simulations [1, 2] much remains to be done. For today is necessary to analyze the experimental data from ECG. These are improved by using the new aquisitons of nonlinear time series [3].

Given the high prevalence and extinguished area of cardiovascular diseases in the last decades, the importance of diagnosis increased proportionally. The accent is put on the ability to record and analysis massive datasets of continuously fluctuating signals. First condition being already accomplished due to technological progress, scientists are focusing actually on analysis of these datasets.

HRV (heart rate variability) or the study of cardiac rhythm fluctuations has attracted the interest of scientists in the recent years for its hypotetical predictive value in the evolution of heart disease.

The electrocardiogram (ECG) is considered the outstanding method of assessing cardiac rhythm for two reasons: first, an ECG is easily recorded and second, the ECG chart of a full cardiac beat shows a characteristic peak, called R peak, due to the ventricular contraction. This peak is high that means easily detectable and narrow localized with high precision. The RR time interval between two R peaks gives the heart beat period, and the RR series (the succession of the RR durations) is the standard tool for measuring a patient's cardiac rhythm. The interest at stake is high, since cardiovascular casualty is a high mortality factor in industrialized countries.

Though ECG, as a complex signal, has been shown to represent processes that are nonlinear, non stationary and non equilibrium -like in nature, the tools used in the conventional analysis still assume linearity, stationarity and equilibrium -like conditions.

Linear systems are predictable. The magnitude of their responses is proportionate with the strength of the stimuli. Further, linear systems can be fully understood and predicted by dissecting out their components .The subunits of a linear system add up - there are no surprises or anomalous behaviors. By contrast, for non-linear systems proportionality does not hold: small changes can have striking or unanticipated effects [7]. Another complication is that non -linear systems cannot be understood by analyzing their components individually, because they interact [5].

In this context, a further integration applied to the signal exaggerates the no stationary character of ECG, often generating errors in diagnosis.

From an engineering point of view, the RR series is just a long discrete signal RR [n] to which signal processing can be applied. If heartbeats were perfectly regular, the RR series would give rise to a constant signal.

The time series obtained by plotting the sequential intervals between beat i and beat i+1, denoted by B(i), reveals a complex type of variability. Cardiac interbeat intervals fluctuate as a complex, apparent erratic manner in healthy subjects even at rest [8].

Therefore, we should find efficient signal processing methods, which distinguish RR series of young patients from the old ones.

Cardiologists first used classical signal processing methods, either "temporal" (calculation of statistical parameters on the RR series), or "frequent" (spectral distribution of energy between high and low frequencies). The development of chaos theory has introduced many new tests meant to detect determinism in a signal and evaluate its complexity: standard methods include phase space reconstruction, Poincare sections, Lyapunov exponents and Kolgomorov entropy [9].

The present paper studies the evolution of long-term correlations in the RR series, quantified by DFA (detrended fluctuations analysis) applied to cardiac rhythm.

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Abstract

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II.METHODOLOGY

II.1 DFA - definition of the method

The calculation procedure for the DFA function (F-DFA) and for its characteristic coefficients (α-DFA) is presented in an article of Peng et al [1].
Details are briefly presented below.

II.2 DFA FUNCTION (F-DFA)

Consider a series B [i], i=1,…,N, for which we want to evaluate the F-DFA. B is the series of RR time intervals between ventricular contractions of heart[1-3].

First, we calculate the indefinite integral of B by:

$$y[k]=\sum_{i=1}^{k}[B[i]-\bar{B}]$$

where $\bar{B}$ is the mean of B assessed over the whole series. The mean B in the formula has no influence on the value of F [n]. It has been introduced for numerical reasons: to limit overflow risks and to prevent small numbers from being added to large ones.

Then, we divide y [k] into windows of equal length n .It is not possible in general to divide exactly the N points of the series into windows of exact length n. For each value of newel n are defining $\tilde{N}$, the larger multiple of n, inferior or equal to N.

Referring to each window, a line segment is fitted to y[k] in the least-squares sense, and we call $y_n[k]$, k=1, N, the concatenation of these successive line segments. Then, in each window, we detrend y [k] by substracting y_n [k] from y[k].

For each n, the value of the F-DFA is defined by:

$$F[n]=\sqrt{\frac{1}{\tilde{N}}\sum_{k=1}^{\tilde{N}}(y[k]-y_n[k])^2}$$

The value characterizes the root mean square fluctuation of the detrended indefinite integral of B[i].

The DFA method normally detrends the data by determining the fluctuations about the least square s best fit straight line in each window of observation. Another way of detrending the data is to modify the DFA algorithm to remove “trends” at all time scales.

Detrending was perform by fitting the data with linear and quadratic polynomials and by then subtracting the fitted curve from the data.

III.2 α-DFA

After performing the mathematical operations described above, it is of major importance to find a power law γn^{α} to fit F [n]. For this purpose, we have to calculate the linear best fit (in the lest square-sense) to the graph of logF versus log n. The slope of this line represents the α-DFA coefficient [8].

For more accuracy, we calculated for each data set two coefficients: α_1, for $4\le n\le 16$ and α_2 for $16\le n\le 64$.

The program that we implemented is in QBasic. Also, the program can be implemented for the other physiological signals: stride gait, EEG, human cognitive process, DNA.

III. RESULTS

III.1 MATERIAL AND METHOD

The ECG was recorded classically and we took them from the databases on Internet [10]. The collection consists of 10 heart beat time series: 11 young healthy subjects and 13 elderly healthy subjects. The length of each recording is approximately 2 hours.

The young (21 - 34 years old) and the elderly subjects (68 - 81 years old) rigorously-screened healthy subjects underwent 120 minutes of continuous supine resting while continuous electrocardiographic (ECG) signals were collected.

The analyses are based on the beat-to-beat heart rate fluctuation of digitized electrocardiograms recorded with an ambulatory (Holter) monitor. Each heartbeat was annotated using an automated arrhythmia detection algorithm, and each beat annotation was verified by visual inspection. The R-R interval (interbeat interval) time series for each subject was then computed.

The study consisted in 22 subjects: 13 old and 11 young. After excluding technically inadequate dates, we used the algorithms above-mentioned to study HRV.

III.2 PRETREATMENT OF DATASET

1. When M [i] is a RR series, it is preferable to apply a pretreatment in order to remove artifacts such as extra systoles or undetected R peaks. Before applying DFA to our RR series, we used the following pretreatment recommended by Goldberger et al. [6]
2. For each set of five contiguous RR intervals, we compute the local mean excluding median interval: RR mean [i] = (RR [i-2] +RR[i-1]+ RR [i+1] + RR [i+2]) / 4.

The central interval, RR [i], is considered to be an outliner unless it lies within a 20% interval around RR mean [i]. Any interval identified as outlier is rejected, and a new RR series is rebuilt with the remaining RR intervals

IV. DISCUSSION

Aging is associated with changes in balance in heart rate variability that may lead to a cause of morbidity and mortality in the elderly.

Previous studies [4] have shown that old subjects have particularly low α_1 and high α_2.

For the first case, when a line segment is fitted to y [k] in the least-squares sense, we obtained the long-range correlation exponent:

- for young subjects:

  $\alpha_1=0{,}97\pm 0{,}26$; $\alpha_2=0{,}96\pm 0{,}18$
- for old subjects:

α_1=0,56 ± 0,23; α_2=0,98 ± 0,31

Based on hypothesis that there is a region of scaling behavior, we obtained the graph:

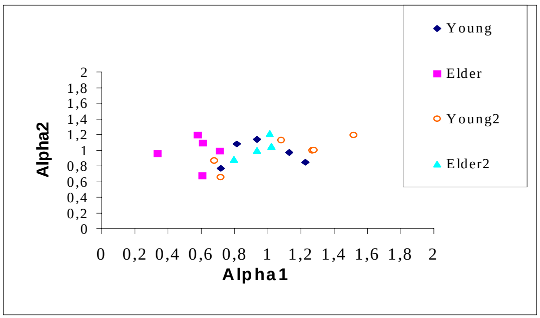

Fig.1. Scatter plot of scaling exponents α_1, α_2 when a line segment is fitted.

For the second case, when a quadratic polynomial is fitted to y [k] in the least-squares sense, we obtained the long-range correlation exponent:

- for young subjects:

  α_1=1,02 ± 0,39; α_2=0,98 ± 0,22

- for old subjects:

  α_1=0,96 ± 0,35; α_2=0,79 ± 0,26

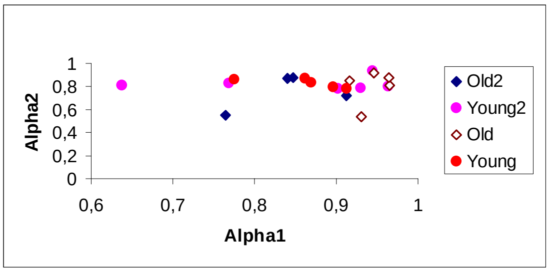

Fig.2. Scatter plot of scaling exponents α_1, α_2 when a quadratic polynomial is fitted.

In the below graph we represented the exponent α_1 for young and elder subjects when a quadratic polynomial and a line segment is fitted.

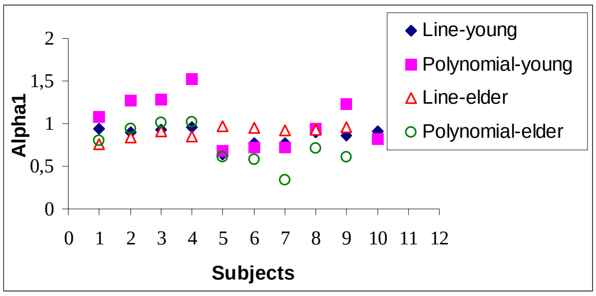

Fig.3. Scatter plot of scaling exponents α_1 for young and elder subjects.

The difference for the elder subjects when a quadratic polynomial and a line segment is fitted for the exponent α_2 is represented in fig. 3.

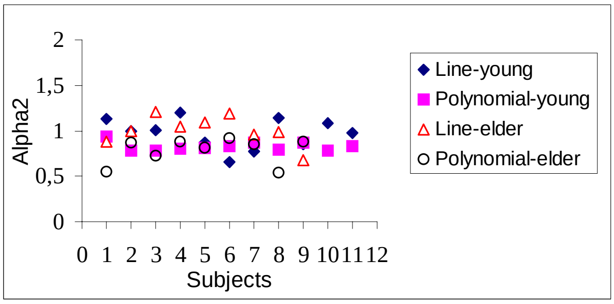

Fig.4. Scatter plot of scaling exponents α_2 for young and elder subjects.

The results of the long-range correlation exponent α_1, α_2 indicate that there is a significant difference in the scaling behavior between young and old states, consistent with a breakdown in long range correlation.

Figures 5, 6, 7 and 8 compare a representative result of fractal scaling analysis of representative 24-hour interbeat interval time series, both with linear and polynomial fitting from a young subject and an old one.

We represented the RR beat intervals (blue) and the parameters α_1 (red), α_2 (magenta).

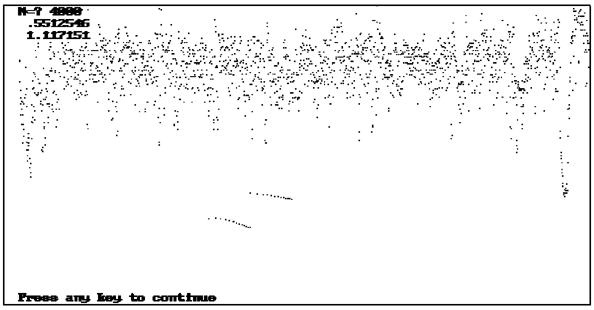

Fig.5. Scatter plot of scaling exponents α_1, α_2 for a young subject when a line segment is fitted to y [k] in the least-squares sense

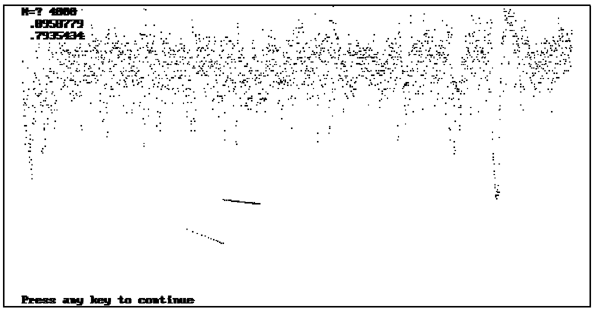

Fig.6. Scatter plot of scaling exponents α_1, α_2 for a young subject when a quadratic polynomial is fitted to y [k] in the least-squares sense.

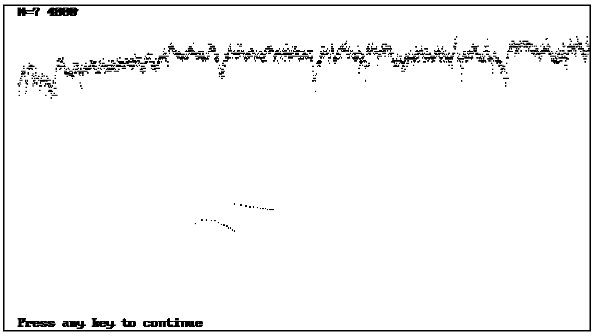

Fig.7. Scatter plot of scaling exponents α_1, α_2 for an elder subject when a line segment is fitted to y [k] in the least-squares sense.

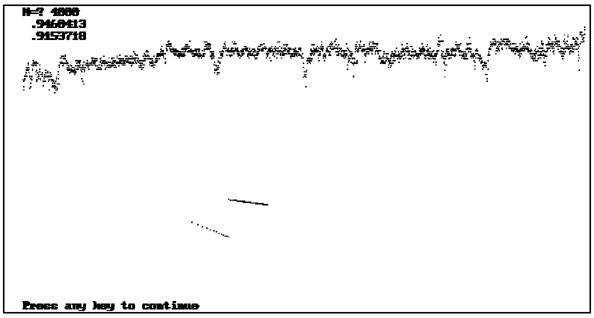

Fig.8. Scatter plot of scaling exponents α_1, α_2 for an elder subject when a quadratic polynomial is fitted to y [k] in the least-squares sense.

The slopes obtained after detrending using second polynomial were virtually identical to the slopes obtained using the first-order linear detrending.

IV CONCLUSIONS

The main conclusions of our study are the following:

- The qualitative analysis with DFA shows different behavior in the group of subjects, both young versus elder. Given the large variety of pathological expressions we found useful the program we implemented in QBasic, following the DFA algorhytm, to separate diseased people, thus improving diagnosis accuracy and estimating primarily the risk of sudden death.
- The analysis was applied to study the effect of physiologic aging. Twelve young (21-34 years) and ten elderly (68-81 years) healthy subjects underwent 2 hours of continuous supine resting ECG recording. In healthy young subjects, the scaling exponent had an value close to 1.0. In the group of healthy elderly subjects, the interbeat interval time series exponents α_1 and α_2 were significantly different, more less, comparative with young subjects.
- Aging is associated with distinctive alterations in the scaling properties which could be of practical diagnostic and prognostic use; the fractal scaling pattern for the elder subject is significantly altered compared with young adults. This mean that physiological aging have effect on the degradation in long-range interbeat interval correlations, specific for every subject;
- If the subjects have close values for α_1, in the case that the line segment is fitted in the least-square sense, we would distinguish the subjects using the second method, when a quadratic polynomial is fitted in the least square sense;
- Fluctuation analysis reveals a marked distinction in how the fluctuations change with time scale for these subjects. The interbeat interval fluctuations are more random (less correlated) for the elderly subject than for the young subject, a difference not detectable by comparing the first and second moments.
- The method in discussion is applicable to improve diagnostic tools or calculating risks, to evaluate the patient's status at a certain moment, being of great importance in estimating recovery of patients with diseases that affect the cardiovascular system and to obtain important information about heart instability among the elderly.
- For the reasons exposed above, those we do not consider these conclusions definitive and we did not finish our study, we recommend the DFA as screening method for the status of cardiovascular system.

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